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An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery

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Abstract. A wide range of urban ecosystem studies, including urban hydrology, urban climate, land use planning, and resource management, require current and accurate geospatial data of urban impervious surfaces. We developed an approach to quantify urban impervious surfaces as a continuous variable by using multisensor and multisource datasets. Subpixel percent impervious surfaces at 30-m resolution were mapped using a regression tree model. The utility, practicality, and affordability of the proposed method for large-area imperviousness mapping were tested over three spatial scales (Sioux Falls, South Dakota, Richmond, Virginia, and the Chesapeake Bay areas of the United States). Average error of predicted versus actual percent impervious surface ranged from 8.8 to 11.4%, with correlation coefficients from 0.82 to 0.91. The approach is being implemented to map impervious surfaces for the entire United States as one of the major components of the circa 2000 national land cover database.

Résumé. Un grand nombre d'études d'écosystèmes urbains incluant l'hydrologie urbaine, le climat urbain, la planification de l'utilization du sol et la gestion des ressources font appel à des données géospatiales à jour et précises sur les surfaces urbaines imperméables. Nous avons développé une approche pour quantifier les surfaces urbaines imperméables en tant que variable continue basé sur l'utilization d'ensembles de données multicapteurs et multisources. Des surfaces imperméables sous forme de pourcentage à l'échelle du sous-pixel, à une résolution de 30 m, ont été cartographiées à l'aide d'un modèle d'arbre de régression. L'utilité, l'efficacité et la rentabilité de la méthode proposée pour la cartographie de l'imperméabilité à grande échelle ont été testées à trois échelles spatiales (les zones de Sioux Falls, au Dakota du Sud, de Richmond, en Virginie, et de la baie de Chesapeake aux États-Unis). Les erreurs moyennes entre les surfaces imperméables estimées en pourcentage versus les surfaces réelles variaient de 8,8 % à 11,4 %, avec des coefficients de corrélation de 0,82 à 0,91. pour l'an 2000. Cette approche est en phase de réalisation pour cartographier les surfaces imperméables de l'ensemble des États-Unis et constitue une des principales composantes de la base nationale de données sur le couvert pour l'an 2000.
[Traduit par la Rédaction]

Introduction

The status and trends of urban land cover and land use significantly impact the quality of human life and urban ecosystems. Accurate, up-to-date, and spatially explicit data on urban land cover and land use are required to support urban land management decision-making, ecosystem monitoring, and urban planning (Ridd, 1995).

One of the most important land cover types characteristic of urban and suburban environment is the impervious surface developed through anthropogenic activities. Impenetrable surfaces, such as rooftops, roads, and parking lots, have been identified as a key environmental indicator of urban land use and water quality (e.g., Arnold and Gibbons, 1996). The spatial extent and distribution of impervious surfaces impact urban climate by altering sensible and latent heat fluxes within the urban surface and boundary layers. Impervious surfaces also increase the frequency and intensity of downstream runoff and decrease water quality. Strong correlation between imperviousness of a drainage basin and the quality of its receiving streams has been reported. For example, stream quality usually starts to degrade if more than 10% of the area of a watershed is impervious (Schueler, 1994).

In recognizing its environmental significance, the impervious surface has been identified as one of the major components of the circa 2000 national land cover data base (NLCD 2000) to be developed through the multiresolution land characteristics (MRLC) 2000 consortium (Homer et al., 2002). The MRLC 2000 consortium was formed to meet the needs of several federal agencies of the United States (U.S. Geological Survey (USGS), U.S. Environmental Protection Agency, U.S. Department of Agriculture Forest Service, National Aeronautics and Space Administration (NASA), and National Oceanic and Atmospheric Administration (NOAA)) for Landsat-7 enhanced thematic mapper plus (ETM+) imagery and land cover – land use data. Through the MRLC 2000 consortium, agencies formed a partnership and pooled resources to develop (*i*) a multitemporal Landsat-7 ETM+ image dataset containing three dates of imagery per path and

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row for the United States, and (*ii*) a consistently developed circa 2000 national land cover database.

Previous studies of urban impervious surfaces

Numerous research efforts have been devoted to quantify urban impervious surfaces using ground-measured and remotely sensed data (Deguchi and Sugio, 1994; Williams and Norton, 2000; Phinn et al., 2000). The methodologies include multiple regression (Forster, 1980; Ridd, 1995), spectral unmixing (Ji and Jensen, 1999; Ward et al., 2000), artificial neural network (Wang et al., 2000; Flanagan and Civco, 2001), classification trees (Smith et al., 2003), and integration of remote sensing data with geographic information systems (Prisloe et al., 2001).

Ridd (1995) proposed a conceptual model, i.e., vegetation-impervious surface soil (VIS), for urban ecosystem analysis. This framework presents a systematic standard for characterizing an urban ecosystem from morphological, biophysical, and anthropogenic perspectives. Using this model, detailed land cover, land use, and biophysical parameters were obtained for urban ecosystems using remote sensing data. Forster (1980) examined the relationship between Landsat multispectral scanner (MSS) data and percent land cover types sampled at the pixel level from the Sydney metropolitan area using multiple regression techniques. Forster found that variables most closely correlated with intensity of urban developed areas were those of normalized band ratios.

More recent studies adopted advanced machine learning algorithms and spectral unmixing that allow the derivation of imperviousness at the subpixel level. For instance, Flanagan and Civco (2001) conducted subpixel impervious surface mapping using artificial neural network and an ERDAS Imagine subpixel classifier. For four municipal study areas in Connecticut, the overall accuracy at impervious–non-impervious detection level varied from 71 to 94%, with a root mean square error (RMSE) of 0.66–5.97%. Wang et al. (2000) developed a subpixel proportional land cover information transformation (SPLIT) model, a modularized artificial neural network based algorithm, to quantify proportion of land cover types from high-resolution multispectral videography. Overall accuracy achieved was 87.6%. Spectral unmixing and classification trees classifier have also been capable of quantifying subpixel impervious surface. The accuracy of imperviousness estimates from unmixing was also comparable (Ji and Jenson, 1999; Ward et al., 2000), whereas overall within-class accuracy using classification trees was about 84% in a study of Montgomery County, Maryland (Smith et al., 2003). Thus far, almost all research conducted was confined within a limited spatial area (one urban setting or at county-level), and each study used only one type of data for developing training data for model prediction.

Research objectives

It was the goal of this research to develop a repeatable, accurate, and cost-effective method to map large-area impervious surface percentage at 30-m spatial resolution for the entire United States. The research presented here describes an alternative approach to extracting subpixel imperviousness information using a regression tree algorithm, Landsat-7 ETM+, and two types of high spatial resolution imagery.

The primary research questions were as follows: (*i*) Is regression tree a reliable and robust algorithm for mapping impervious surfaces nationwide? (*ii*) What are the optimal input variables for modeling impervious surfaces, and are they scale-dependent? (*iii*) Can a regression tree model developed using training data from one particular location be applied to another area with a broader scale? (*iv*) Is the high spatial resolution imagery a cost-effective data source for deriving training–test data for large-area impervious surface mapping?

Data and preprocessing

Study area

The proposed procedure was tested in three geographic areas within the United States representing different spatial scales: Sioux Falls, South Dakota (local scale of ~1000 km^2), Richmond, Virginia (subregional scale of ~10 000 km^2), and Chesapeake Bay of the eastern United States (regional scale of ~100 000 km^2).

Data

Landsat-7 ETM+ images were the primary data source for mapping impervious surfaces. Data quality of Landsat-7 ETM+ is superior to its predecessors (e.g., Landsat-5), with significant improvement of on-flight radiometric and geometric calibration, inclusion of a 15-m resolution panchromatic band, and an improved 60-m spatial resolution thermal infrared band.

Two types of high spatial resolution images, IKONOS from Space Imaging and the digital orthophoto quadrangles (DOQ) of the U.S. Geological Survey scanned from the National Aerial Photography Program (NAPP) color infrared photographs, were utilized for derivation of training–test data. With a nominal spatial resolution of 1 m, the DOQ image has three bands: green, red, and near infrared (detailed information on the DOQ images is available at <http://edc.usgs.gov/glis/hyper/guide/usgs_doq>).

Table 1 lists all Landsat data used for each of the three study areas. For Sioux Falls, a leaf-on (June 2000), cloud-free IKONOS image covering the city and surrounding areas was available for deriving training–validation data. A Landsat-7 ETM+ scene that covers the same area and is only 1 day apart from the IKONOS data acquisition date was also available along with another leaf-off (October 2000) image. Coincidence of time and similar spectral bandwidth of the two data sets

Table Landsat-7 ETM+ imagery utilized for imperviousness mapping

Location	Path	Row	Spring	Summer	Fall
Virginia		34		28 July 1999	17 Nov. 1999
		34		19 July 1999	8 Nov. 1999
Sioux Falls		30		30 June 2000	20 Oct. 2000
East coast		32–35	March–April 2000–2001	July 1999	Sept.–Oct. 1999–2000

provided good opportunities for testing impervious surface mapping at a local scale.

Similar to Sioux Falls, Landsat ETM+ data available for the Richmond study included two scenes (one leaf-on and one leaf-off). The high-resolution data used for deriving training and test data were the DOQs acquired in spring of the late 1980s to early 1990s.

For the Chesapeake Bay study, nine ETM+ scenes were required to cover the entire area. Three Landsat images (spring, summer, and fall) were available for each path and row. The training data source was the DOQs acquired in spring and summer of the late 1980s to 1990s.

Image preprocessing

All ETM+ data preprocessing followed standard specifications, including (*i*) radiometric and geometric calibration and terrain correction (Irish, 2000), (*ii*) conversion from digital number to at-satellite reflectance (for six reflective bands) or at-satellite radiance temperature (the thermal band), and (*iii*) referencing to the National Albers equal-area map projection and resampling using cubic convolution to 30-m resolution. After initial preprocessing, tasseled-cap brightness, greenness, and wetness were derived using at-satellite reflectance-based coefficients (Huang et al., 2002).

For IKONOS data the 1-m panchromatic data were fused with 4-m multispectral bands, resulting in an image of four bands (blue, green, red, and near-infrared (NIR)) with "sharpened" spatial resolution of 1 m. Both IKONOS and DOQ data were in universal transverse Mercator (UTM) projection and were reprojected to Albers equal-area projection. To ensure a high degree of accuracy in image coregistration (between high-resolution imagery and the Landsat-7 ETM+ imagery), exact projection transformation was used. Visual inspection revealed that misregistration errors between the DOQ–IKONOS and the ETM+ images were generally less than one ETM+ pixel.

For the Chesapeake Bay area, additional data preprocessing was done by Earthsat Corporation (under USGS contract 010112C0012) to mask clouds and cloud shadows and hazy areas. Spectral values of each ETM+ band of the masked areas were subsequently estimated based on cloud-free images from the other two dates using regression tree techniques. Specifically, the cloud mask was used to subset out areas of clouds for each individual band for any one date or all dates of imagery. Within the subset areas of one image, each band was then individually estimated through a regression tree algorithm using ETM+ imagery of the other two dates. After all bands were processed, the estimated digital data were merged with the original data band by band. This ensured that as many of the original pixel values remained unchanged as possible, while all cloud covered pixels were replaced with estimated data. This process was deemed necessary because per-pixel mapping required noncontaminated reflectance data and spatially continuous estimates were desired.

Methods and procedures

The proposed methodology for impervious surface mapping consists of several steps: (*i*) algorithm selection, (*ii*) training and validation data development, (*iii*) predictive variable selection and initial regression tree modeling and assessment, and (*iv*) final modeling and mapping (**Figure 1**).

Regression tree algorithm

The general classification and regression tree (CART) algorithm conducts a binary recursive partitioning process. The process splits each parent node into two child nodes and the process is repeated, treating each child node as a potential parent node (Breiman et al., 1984). The regression tree algorithm produces rule-based models for prediction of continuous variables based on training data. Each rule set defines the conditions under which a multivariate linear regression model is established. Regression tree models can account for a nonlinear relationship between predictive and target variables and allow both continuous and discrete variables as input variables. It has been reported that accuracy and predictability of the regression tree models were better than those of the simple linear regression models (Huang and Townshend, 2003). The regression tree algorithm we used to model impervious surfaces is a commercial software called Cubist,[2] which is one type of regression tree algorithm (detailed information on Cubist software is available at <http://rulequest.com/cubist-info.html>).

The quality of the constructed regression tree can be measured by an average error R of a tree T, expressed by

$$R(T) = \frac{1}{N} \sum_{i=1}^{n} | y_i - g(\vec{x}_i)|$$

where the function $g(\vec{x}_i)$ represents the regression plane through the example set, N is the number of samples used to establish the tree, and y_i is the actual value of the predicted variable.

[2] Use of any trade, product, or company names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

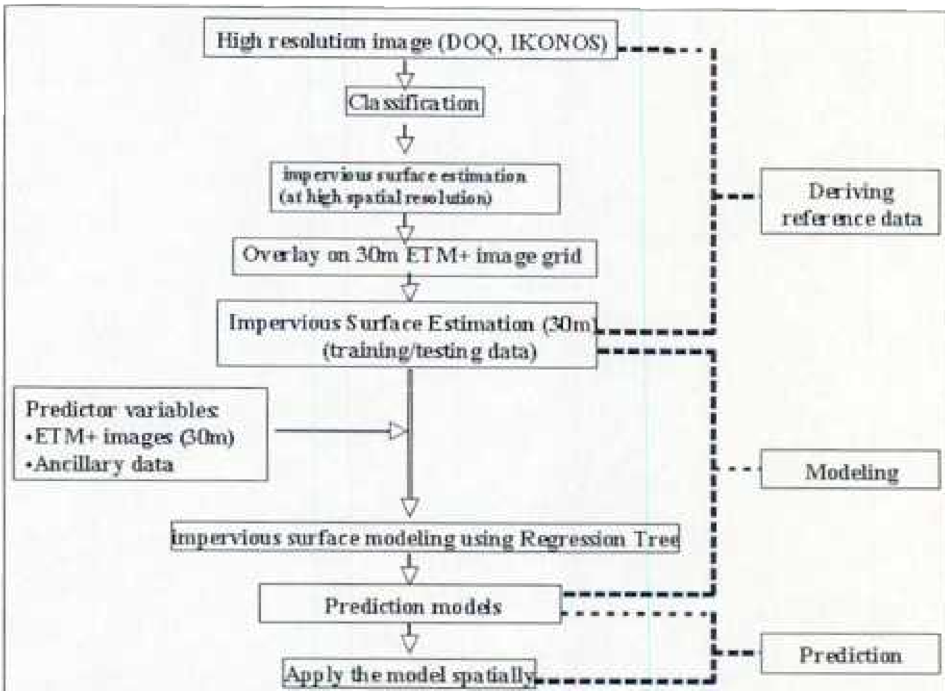

Figure 1. The proposed procedure for impervious surface mapping using Landsat-7 and high spatial resolution imagery and a regression tree model.

To compare the quality of several regression trees, a relative error is often used and is defined as

$$\mathrm{RE}(T) = \frac{R(T)}{R(\mu)} \tag{2}$$

where $R(\mu)$ is the average error that would result from always predicting the mean value. It is used to standardize the average error, $R(T)$.

Besides the average error and relative error, Cubist also calculates the product-moment correlation coefficient (r) between the actual and predicted values. All three statistical measures were used throughout the study to evaluate model performance.

Another feature of Cubist is its ability to estimate predictive accuracy by n-fold cross-validation. Using this option the training data set can be divided into n blocks of roughly equal size. For each block in turn, a model is built from the data in the remaining blocks and tested using the holdout block. The final accuracy of the model is estimated by averaging model results from all n-fold tests (Michie et al., 1994).

Training–test data collection

Successful modeling using regression tree techniques relies on the quality of training–test data. In this study, training data selection was constrained by potential data availability nationwide. A large number of training data were collected for each study area representing spectral and spatial variability of impervious areas due to differences in building materials, ages, surface colors, and spatial orientation.

For Sioux Falls, four subset windows of approximately 2000 × 2000 m each were selected from the IKONOS image. Training and test data of impervious surfaces were obtained by an unsupervised clustering algorithm. Each cluster was interpreted and labeled with one or more of the five land cover classes (water, vegetated areas, bare soil, impervious surfaces, and shadow) and was further modified by screen digitizing and recoding to reduce misclassification. A final product was a binary raster image of impervious versus nonimpervious pixels at 1 m.

Training and test data for Richmond were derived from four DOQ image windows (1800 × 1800 m each). Three of the windows were in the metropolitan Richmond area and the other was in City Farm located in the west part of the study area. These image windows were visually selected to capture spectral variation of impervious surfaces and to avoid areas where land cover changes occurred between the acquisition of the DOQ and the ETM+ images.

The selected DOQ images were classified using a decision tree classification program called C5 (Quinlan, 1993). Each pixel was classified as one of five land cover classes: impervious surface, forest, grass, water, and shadow. The classifications were manually edited to correct confusions between impervious surfaces and other classes. The reference data derived from each DOQ image were then divided into nine equal-sized blocks, six of which were randomly selected for use as training data and the remaining as test data. Using randomly selected pixel blocks rather than individual pixels as test data should reduce possible bias in model accuracy assessment due to spatial autocorrelation between training and test data (Campbell, 1981; Friedl et al., 2000).

For the Chesapeake Bay area, a special module was developed by Earthsat Corporation to select training and test data based on spatial and spectral characteristics of the imagery and impervious surface. The selection process took into account spectral variance accounted for by each selected sample and continued to add samples until the variances captured reached a predefined threshold. As a result, the process selected 20 DOQs, and a portion of each DOQ was classified into impervious surfaces using a combination of unsupervised–supervised methods with some manual editing and recoding.

For all three study areas, once the final classification was made, all 1-m pixels mapped as impervious surface were tallied using a 30 × 30 m grid geographically aligned with ETM+ pixels to compute percent impervious surfaces. In this process, the IKONOS (or DOQ) 1-m pixel whose coordinates matched that of the upper left ETM+ pixel was used as the starting point of the 30-m grid. One-metre shadow class pixels were excluded from the percent impervious calculation within each 30-m pixel.

Predictive variable selection and initial regression tree modeling

An initial regression tree model was developed using training data obtained from the high-resolution data. It involved two tasks, feature selection for most relevant input variables and preliminary regression tree modeling. Both tasks were accomplished using the Cubist software. Although all spectral bands could be input to Cubist, using fewer variables to reduce data volume and computing time was desirable. The relative importance of the predictive variables was assessed based on their position within a multivariate linear regression at a given tree node, because the variables were ordered in decreasing relevance to the percent imperviousness.

Once the initial prediction was made, quality control was performed. The predicted percent impervious surface was evaluated through cross-validation and by using holdout test data and visual inspection of the predicted maps. For areas where the magnitude of overprediction and (or) underprediction exceeded 10%, additional training samples were selected and a new model built to improve prediction.

Final regression tree model and mapping

The final regression tree model was built using the most relevant input variables and all available training data, and then applied to all pixels to map percent impervious surfaces. Accuracy of the final model was obtained through validation using holdout test data. From the sampling point of view, the validity of an accuracy estimate depends on whether the test data are collected using a probability-based sampling design. Ideally, the training data for model calibration and test data for model evaluation are obtained from different sources and are spatially independent. Due to the large spatial scale dealt with by this study, the derived 30-m reference data from high-resolution images were used for both training and validation purposes. Each high-resolution reference data image was divided into equal-sized blocks, with two thirds of the blocks randomly selected as training samples and the remaining reserved as test samples. Splitting the reference points by pixel block rather than by pixel reduced the spatial autocorrelations between training and test samples. For each study area the training samples from all windows were combined to form a training data set and the test samples combined to form a test data set. Because the test data were not used to build the regression tree model, all test error estimates (mean absolute error and relative error) generated by the Cubist software were considered reliable.

Final products consisted of (*i*) spatial estimates of subpixel percent imperviousness at 30-m resolution, (*ii*) rule sets on conditions under which each prediction model was built, and (*iii*) error estimates of the prediction through validation.

Results

Sioux Falls, South Dakota

Several regression tree models were built by Cubist using combinations of different input variables (14 ETM+ spectral bands and 6 tasseled-cap transformed bands from leaf-on and leaf-off images). **Table 2** lists accuracy estimates, through cross-validation, when various combinations of input variables were used. The correlation coefficients ranged from 0.82 to 0.89, with an average error of 9.2–11.4%. In most cases, changes in accuracy estimates were rather small, suggesting the use of fewer input variables.

Analysis of rule-sets from the model output revealed that the most important variables were tasseled-cap greenness, band 4 (NIR), band 7 (middle infrared (mid-IR)), and band 3 (visible) of the leaf-on image. Thus, the final regression tree model was built using leaf-on data only and applied to map the entire city of Sioux Falls.

Visual inspection revealed that the spatial pattern of modeled impervious surface was quite reasonable (**Figure 2a**). Major urban centers and a shopping mall complex were predicted with the highest percent imperviousness. The model also correctly predicted different intensity in development between the old and the newly developed residential areas. A major weakness of the model prediction was at the edge of the city where some bare soil was mapped as the medium to high imperviousness due to spectral confusion.

Another way to evaluate model performance is to directly compare mapped imperviousness against that derived from the set-aside high-resolution data. **Figure 2b** shows a comparison in an area in southeastern Sioux Falls. Estimated percent imperviousness of major roads, school buildings, and residential houses compared favorably with those estimated using high-resolution data. In most cases the difference is within 10% or less.

Table 2. Estimation of mean average error (MAE) and correlation coefficient (r) for Sioux Falls, South Dakota, using various combinations of predictive variables.

Test	onb1–6	offb1–6	onb7	offb7	onTC	offTC	MAE (%)	r
								0.89
2								0.88
3						×		0.85
4			×					0.89
5			×			×		0.88
6	×		×					**0.88**
7								0.85
8			×					0.87
9								0.82

Note: onb1–6, six bands total from leaf-on ETM+ visible, NIR, and mid-IR bands; offb1–6, fall ETM+ visible, NIR, and mid-IR bands; onb7, leaf-on ETM+ thermal band; offb7, fall ETM+ thermal band; onTC, three bands total from leaf-on tasseled-cap bands (brightness, greenness, wetness); offTC, three bands total from fall tasseled-cap bands (brightness, greenness, wetness). A regression tree model built from test 6 was used to map spatial distribution of impervious surfaces.

Richmond, Virginia

Several regression tree models were built by using different combinations of spectral bands and band ratios. Based on evaluations using hold-out data (6962 pixels), the model developed using a minimum number of five bands, i.e., leaf-on bands 1, 4, 5, 6, and 7, was almost as accurate as those developed using more bands (by adding those of the second and third power of the original ETM+ spectral bands and a texture band). The accuracies of different models differed only slightly, with correlation coefficients ranging from 0.88 to 0.91 and average error from 8.8 to 10.0% (**Table 3**). Therefore, a final model was made using a subset of leaf-on spectral bands only (bands 1, 4, 5, and 7 and a thermal band).

Visually, the model predictions were quite reasonable in an urban area located within the two scenes, including Richmond, Petersburg, and a part of Newport News and Frederick in the east and Charlottesville and Lynchburg in the west (**Figure 3a**). Outside the urban areas, however, the model did predict a considerable amount of imperviousness in some fallow fields and bare ground. Much of the problems should be fixable if an accurate non-urban mask is available. We made some efforts to create an urban mask in a subsequent study.

As one of the research objectives, we tested whether a model developed from one city can be applied to another city. To do this, a regression tree model established using Sioux Falls training data was applied to the Richmond area.

Figure 3 shows, to a large extent, a similar pattern between two imperviousness maps (**Figure 3b** shows the prediction using the regression model built from the Sioux Falls training data, and **Figure 3a** shows the prediction using the Richmond training data). The areas with a high impervious surface were similarly mapped by using the two models, probably due to the fact that both cities are located in the mid-latitude with minimum topography. The main differences between the two were found in the low- to medium-intensity developed areas, where percent impervious surfaces estimated using the Sioux Falls model was higher than that predicted using the Richmond training data. Further checking using high-resolution DOQ suggested that the average of the overprediction using the Sioux Falls model was about 10%. The discrepancy is likely due to differences between the ETM+ images of the two locations. The presence of haze within the leaf-on image of Richmond resulted in high spectral values of the three visible bands. Because visible bands were mostly positively correlated with the percent impervious surface in the Sioux Falls model, when applied to Richmond the higher values of the visible bands caused an overestimation.

The results of this test imply a possibility to spatially apply an impervious model to a different area with similar intensity in urban development using good quality images with minimum topographic and atmospheric impacts.

Chesapeake Bay area

To test the robustness and feasibility of the method when applied to large areas, several regression tree models were built for the Chesapeake Bay area by Earthsat Corporation (under USGS contract number 010112C0012). Model evaluations using holdout data resulted in correlation coefficients varying from 0.87 to 0.90, with average error from 8.8 to 10.2% (**Table 4**). Quantitatively, 200 000 pixels within the training DOQs were randomly selected and used to assess model prediction by comparing model-predicted and actual values. The result showed that the error was near normally distributed, and approximately 70% of the samples fall within 18% of the absolute error bound (**Figure 4**).

Overall, estimation of percent imperviousness improved with the ETM+ image of all three dates utilized. Use of three tasseled-cap bands performed equally well as compared with the results obtained using all six spectral bands. The final impervious surface layer was produced using tasseled-cap transformed bands from all three dates and a leaf-on thermal band.

Judging by spatial pattern, the overall performance of the model was satisfactory (**Figure 5**). In particular, the model predicted well for areas with medium to high imperviousness, extending from the Philadelphia – Baltimore – Washington,

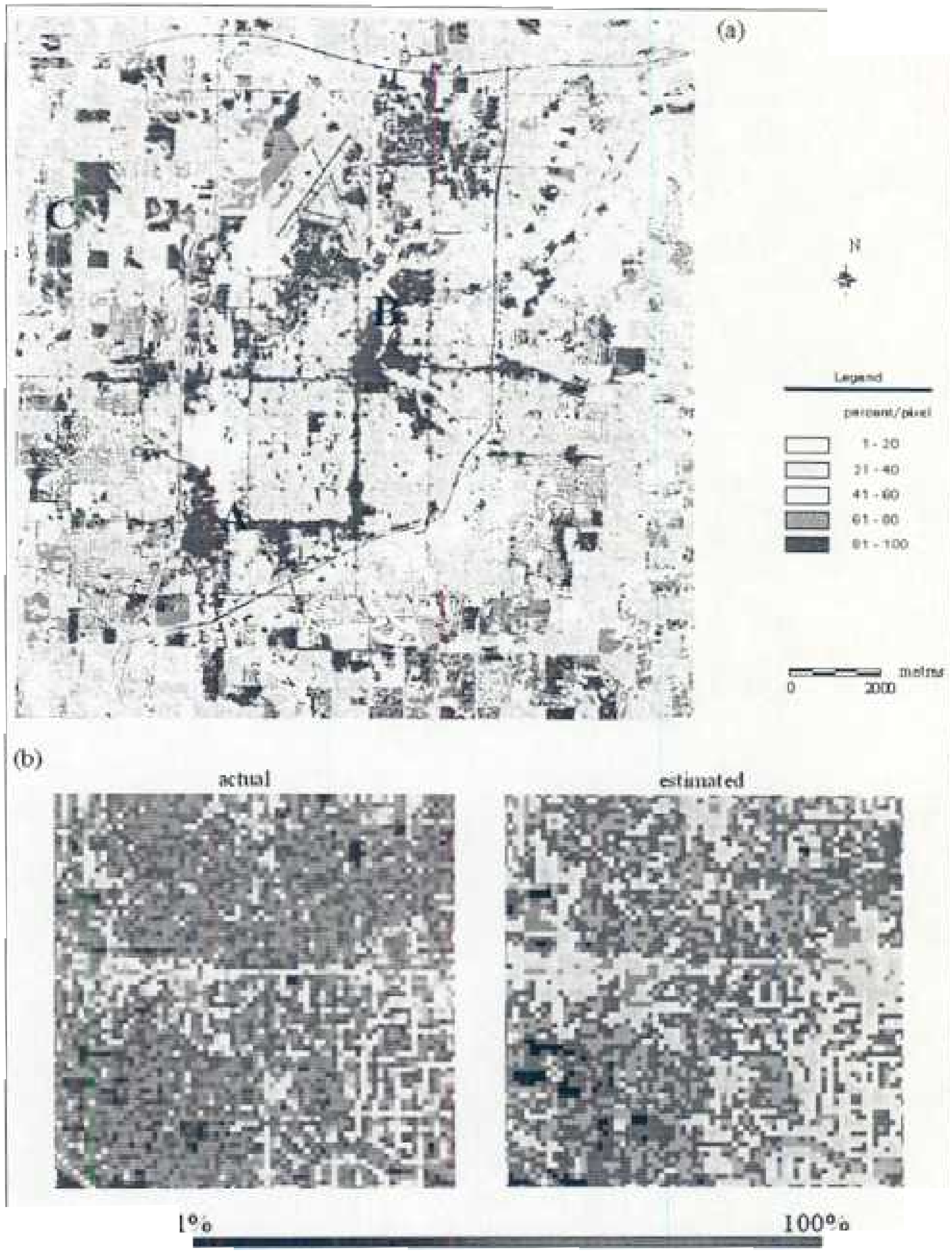

Figure 2. (a) Spatial prediction of subpixel percent imperviousness for Sioux Falls, South Dakota. A, shopping mall complex; B downtown; C, bare field. (b) Comparison of model-estimated subpixel percent imperviousness versus that derived from the high spatial resolution image (IKONOS) in southeastern Sioux Falls.

D.C., metropolitan areas to their surroundings. Areas mapped as lower–medium imperviousness were mostly reasonable but with notable commission errors in some bare fields.

Since our ultimate goal is to map the impervious surfaces nationwide, a major challenge is to accurately map imperviousness of all urban areas and, at the same time, minimize commission errors. Towards this end, we tried to develop an urban mask from several ancillary data layers. One of these was a raster image of cities derived from the NOAA Defense Meteorological Satellite Program (DMSP) night light data (Elvidge et al., 1997). Another one was an aggregate of urban land cover – land use classes from the USGS 1990 national land cover dataset (Vogelmann et al., 2001). Both images were of 1-km spatial resolution. In addition, a vector file of the TIGER 2000 roads from the U.S. Census Bureau was buffered and combined with the two raster images. Although useful, this urban–road mask was problematic in some areas due to the coarse spatial resolution of the images and road buffers.

Table 3. Estimation of mean average error (MAE) and correlation coefficient (r) for Richmond, Virginia, using various combinations of predictive variables.

Test	onb1–6	offb1–6	onb7	offb7	onTC	offTC	MAE (%)	r
	×	×			×	×	8.8	0.91
	×	×					8.8	0.91
3					×		10.0	0.88
4					×		9.5	0.89
5					×		9.4	0.90
6							**9.1**	**0.90**
7						×	9.2	0.90

Note: onb1–6, six bands total from leaf-on ETM+ visible, NIR, and mid-IR bands; offb1–6, fall ETM+ visible, NIR, and mid-IR bands; onb7, leaf-on ETM+ thermal band; offb7, fall ETM+ thermal band; onTC, three bands total from leaf-on tasseled-cap bands (brightness, greenness, wetness); offTC, three bands total from fall tasseled-cap bands (brightness, greenness, wetness). A regression tree model built from test 6 was used to map spatial distribution of impervious surfaces.

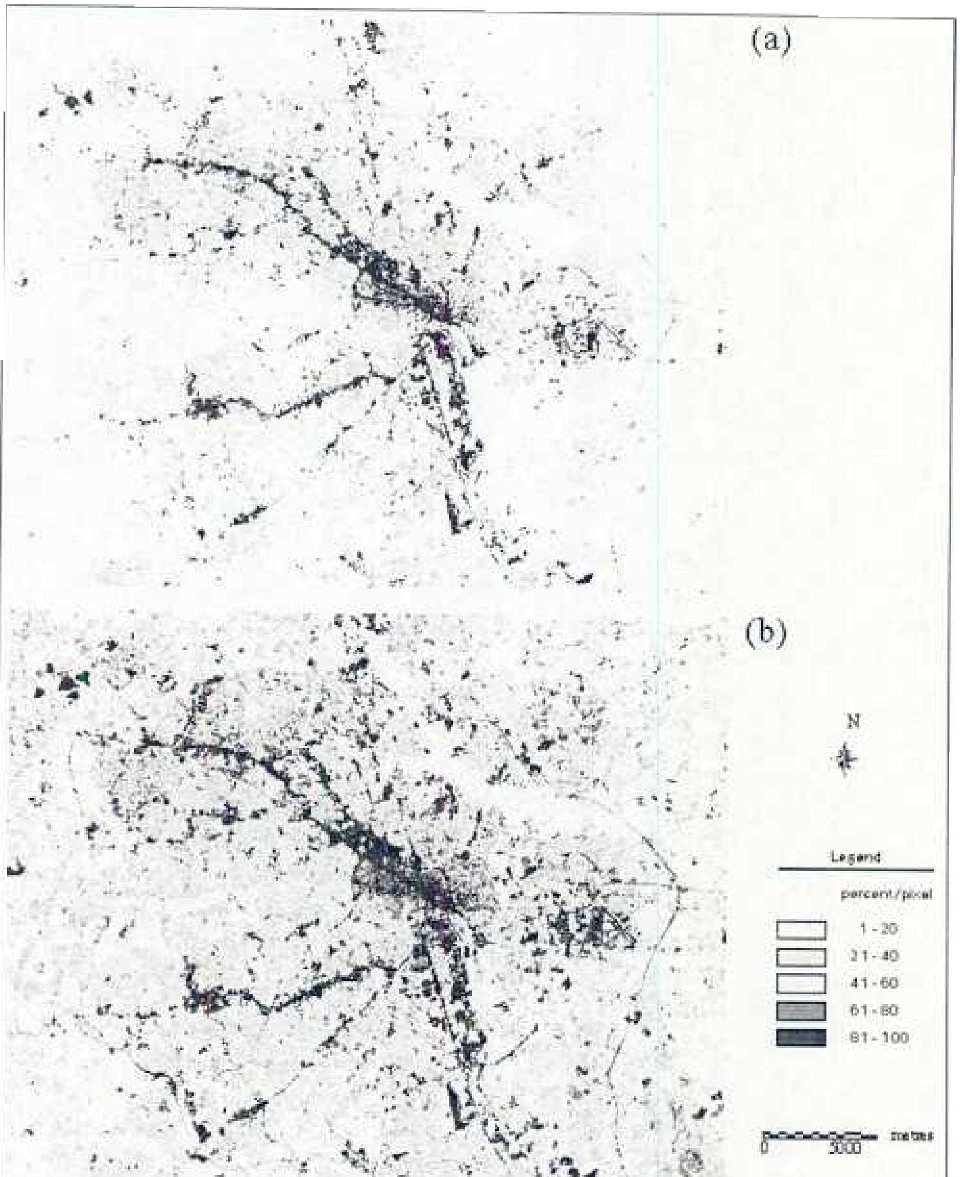

Figure 3. Spatial prediction of subpixel percent imperviousness for Richmond, Virginia: (a) from the prediction using the Richmond model, and (b) from the Sioux Falls model.

Table 4. Estimation of mean average error (MAE) and correlation coefficient (r) for the Chesapeake Bay area using various combinations of predictive variables.

Test	onb1–7	offb1–7	spb1–7	onTC	offTC	spTC	MAE (%)	r
1	×	×					9.0	0.89
2	×	×	×				8.8	0.90
3				×	×		10.2	0.87
4				×	×	×	9.3	0.88

Note: onb1–7, seven bands total from summer ETM+ bands; offb1–7, seven bands total form fall ETM+ bands; spb1–7, seven bands total from spring ETM+ bands; onTC, three bands total from summer tasseled-cap bands (brightness, greenness, wetness); offTC, three bands total from fall tasseled-cap bands (brightness, greenness, wetness); spTC, three bands total form spring tasseled-cap bands (brightness, greenness, wetness). A regression tree model built from test 4 was used to map spatial distribution of impervious surfaces.

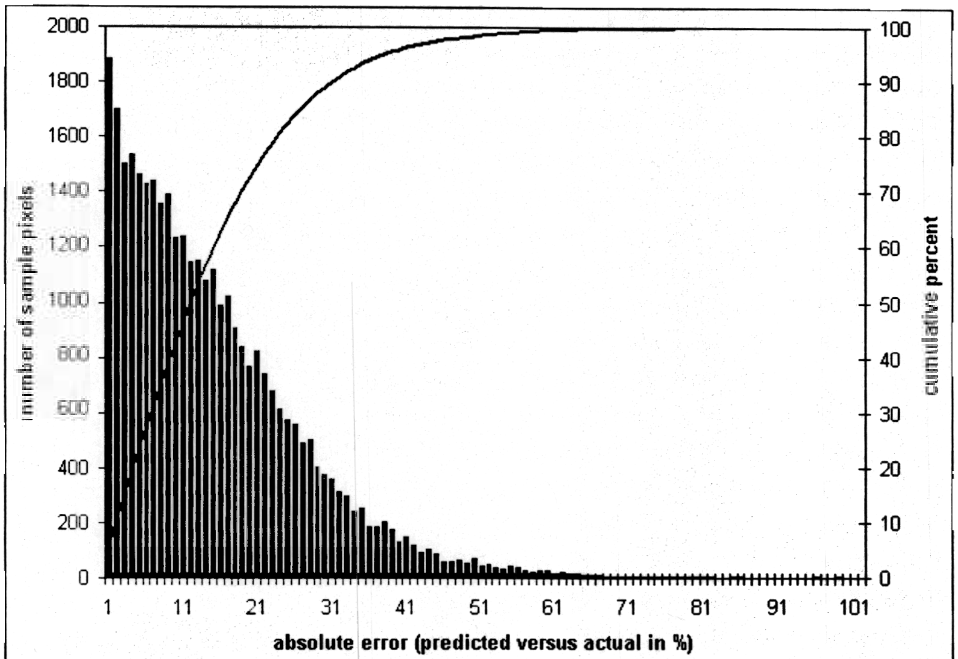

Figure 4. Histogram and cumulative percentage of absolute error between predicted and actual percent imperviousness using sampled pixels from the Chesapeake Bay study area.

Conclusions

We developed an approach to quantifying impervious surfaces as a continuous variable using Landsat ETM+ and high-resolution imagery. Estimates of percent impervious surface at the subpixel (30 m) level were modeled and spatially mapped using a regression tree algorithm. Three geographic areas representing local, subregional, and regional scales were tested using this method, and the model performance was assessed through holdout data not used to build the models.

Regardless of change in spatial scale, the regression tree was capable of predicting imperviousness with consistent and acceptable accuracy. For all three areas tested, the correlation coefficient between model-predicted and actual percent impervious surface ranged from 0.82 to 0.91, and the average error varied from 8.8 to 11.4%. Because the procedure was mostly automated and took only limited computing time, we believe that the method is cost-effective and suitable for large-area imperviousness mapping.

Using spectral bands from both leaf-on and leaf-off imagery usually improved model prediction, but only to a limited extent. When only a single image was used, the regression tree was still able to predict impervious surfaces without significant loss in accuracy. The use of tasseled-cap transformation bands reduced the number of input variables without compromising quality of the final product. For all three tests, the most relevant set of input variables in model prediction were one band each in the visible, NIR, and mid-IR spectra or the three tasseled-cap bands. In addition, using either DOQ or IKONOS as training data showed little difference in terms of accuracy predicted using a regression tree algorithm.

Applying the regression tree model developed from one urban area to another urban area with similar geographic settings may be possible provided that the input ETM+ images for both areas are acquired in the same season with little atmospheric impact (clouds and haze). This spatial extensibility may be beneficial in large-area impervious surface mapping because training–validation data can be quite

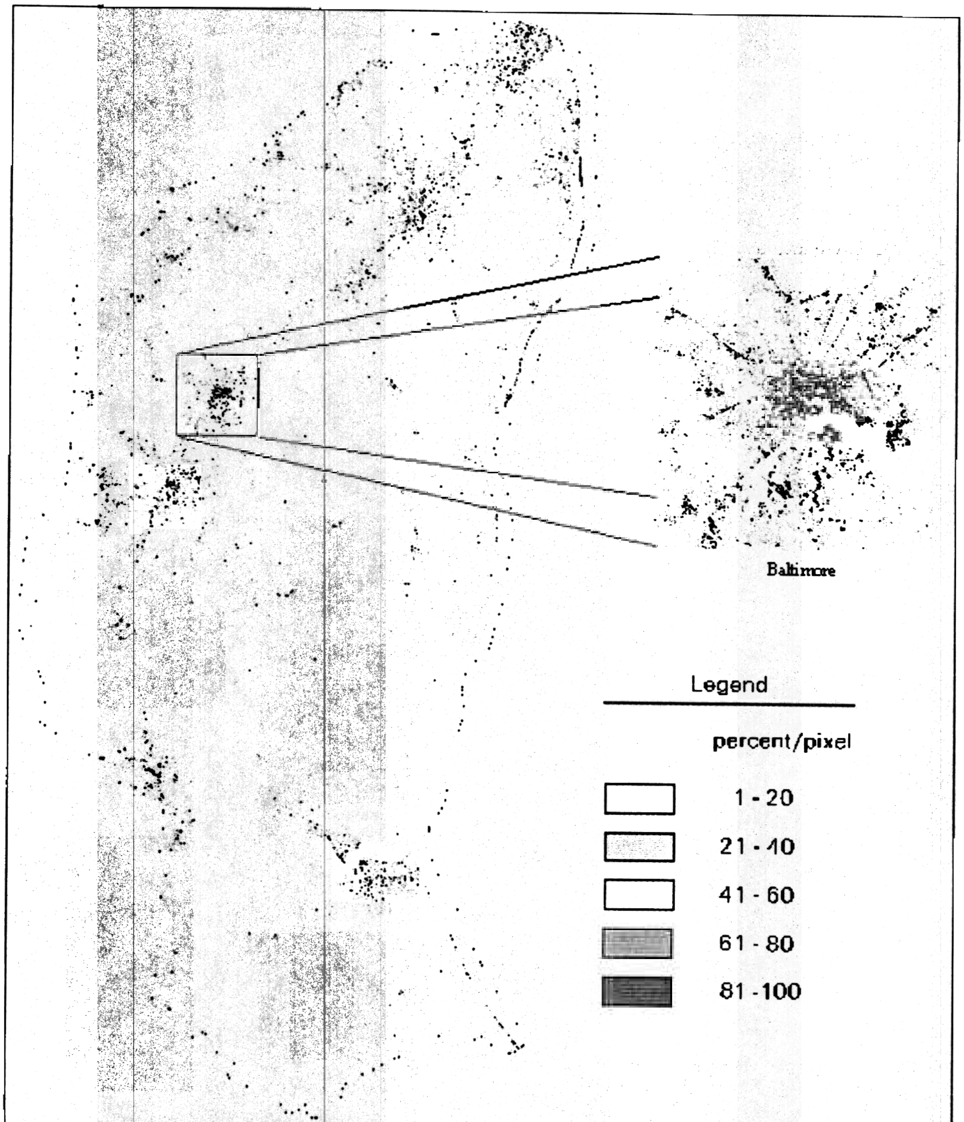

Figure 5. Spatial prediction of subpixel percent imperviousness for the Chesapeake Bay study area.

expensive to obtain, and in some cases may not even be available. It should be noted, however, that we have only tested one pair of cities, and hence the results are not conclusive. Further tests are needed in other urban areas with different environmental settings (e.g., arid or tropical areas) to fully understand this issue.

In this study, all validation of the regression tree models was made through cross-validation and (or) independent data. For large-area impervious surface mapping, collecting field-based measurements for training–test data is likely cost-prohibitive. High-resolution imagery provides an alternative. It is important to use a probability-based sampling protocol for selecting validation data from an image. In this way, the validation data will be independent from the training data with minimum spatial autocorrelation (Friedl et al., 2000).

In all three tests of varying spatial extent, commission errors in mapped impervious surfaces occurred due to similar spectral properties among bare fields, county roads, some rocks – sand beach, and urban built-up areas. This is an issue in particular for large-area mapping and is yet to be resolved. One possible improvement is to develop an accurate urban mask based on satellite imagery with spatial resolution better than 1 km and other ancillary data (e.g., an up-to-date version of the U.S. 2000 census data).

Methods developed from this pilot study have been revised and implemented for the operational phase. The production of NLCD 2000 is proceeding using mapping zones defined based on ecological and environmental characteristics. Subpixel impervious surface estimates of two mapping zones were finished in January 2002, with completion for the entire United States targeted for 2005.

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